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Farmers' interest and willingness-to-pay for index-based crop insurance in the lowlands of Nepal

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ABSTRACT

Farmers in Nepal face many risks from extreme weather events which detrimentally impact their crop production. To support farmers in risk management, prevent financial losses, and facilitate farmer participation in insurance schemes, the Nepalese government subsidises crop insurance by paying 75% of the premiums. However, the uptake of insurance schemes has been poor. This study aimed to find out why by surveying 350 farmers, and identifying factors that influenced farmers' general interest in, and willingness-to-pay for, crop insurance. Approximately 84% of farmers' were interested in purchasing area-based crop yield insurance and were, on average, willing to pay a premium of USD 42.42/ha/cropping season for paddy rice, and USD 29.52/ha/season for wheat. This amounted to more than three times the price of paddy rice premiums (USD 9.96/ha/season), and nearly three times that of wheat premiums (USD 8.59/ha/season) under the current subsidised scheme. This implies that the cause of low uptake is unlikely to be related to the price of premiums. The results further suggest that in order to increase farmers' uptake of crop insurance, the information of the threats of climate variability to future crop failures should be better communicated; and that the current subsidised insurance scheme should be revised.

1. Introduction

Climate change is expected to lead to rising temperatures and increasing climate variability, including frequent and intense extreme weather events (EWEs) such as heat waves, droughts, flooding, and cyclones or other heavy storms (Field et al., 2014). Extreme weather events have detrimental impacts on agricultural production, food security, and livelihood, particularly in developing countries (Hanjra and Qureshi, 2010; Devkota et al., 2013; Pandey and Bardsley, 2015). Droughts and extreme heat, for example, have reduced national cereals production by 9–10% across the globe between 1964 and 2007 (Lesk et al., 2016). In the future, people in developing countries, such as Nepal, are expected to suffer the most in the future from climate-related extreme events, due to their heavy dependence on the traditional subsistence agricultural sector (Aryal et al., 2014), as well as a limited adaptive capacity due to poverty and a lack of access to information and disaster support (Wheeler and von Braun, 2013; Devkota and Maraseni, 2018). Without sufficient adaptation measures against the impacts of EWEs, there will be substantial losses in crop productivity, particularly in southern Africa and southern Asia (Lobell et al., 2008; Yuzva et al., 2018). Governments and other stakeholders in these regions should focus on strengthening agricultural growth and eliminating poverty through sound policy-making and investments in better risk management, to help farmers cope with EWEs in the long-run (Dawson et al., 2011).

Sharing the burden of financial risk from yield losses can be achieved through agricultural insurance (Miranda, 1991; Binswanger-Mkhize, 2012; Mahul et al., 2012; Mobarak and Rosenzweig, 2012). There are two types of insurance: traditional loss-based schemes and index-based schemes (Carter et al., 2014; Yuzva et al., 2018). Many developing countries have abandoned individual loss-based crop insurance because these insurance mechanisms are not viable due to high transaction costs (Skees et al., 1997; Greatrex et al., 2015), and have, therefore, adopted index-based schemes, which are now the most commonly used. In index-based insurance, payouts are based on easily measurable environmental conditions, an 'index' that is closely related to agricultural production losses (Greatrex et al., 2015).

Among the various index-based insurance schemes, the two most common for crop yields insurance are weather-based index insurance and area-based yield insurance. Weather indices can register days of

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rainfall or drought, and farmers receive a payout when the particular index exceeds a set threshold in their area (Binswanger-Mkhize, 2012). In area-based yield insurance, payouts are based on village level yields, whereby the policyholder receives an indemnity whenever the village yield falls below a specified threshold, regardless of their own farm yield (Barnett et al., 2005).

Despite the potential positive impacts of index-based insurance, the outreach and uptake are low in many developing countries, including Nepal. Less than 0.3% of farmers in low- and middle-income countries have agricultural insurance (Mahul and Stutley, 2010). Farmers are aware that when depending on an index, the risk might be lower than expected and they would expect and need to cover their actual losses (Yuzva et al., 2018). In addition, as farmers do not have enough information about the mechanism behind such an insurance scheme, they are unable to judge if it would be beneficial to them or not (Binswanger-Mkhize, 2012).

In their uncertainty, they instead rely on their own adaptation strategies. Even if farmers have knowledge of the schemes, the cost calculations are perceived to be very complicated, and issues of moral hazards might occur (Carter et al., 2014). To increasing the rate of insurance adoption, there needs to be a better understanding about how farmers perceive the potential benefits of index-based insurance and how much they can afford to pay for premiums to cover potential yield losses in case of EWEs. Closing this gap between payouts and perceived losses will help to increase the demand for index-based insurance (Elabed and Carter, 2015).

The aim of this study was 1) to assess farmers' general interest in participating in an index-based insurance scheme, 2) to reveal how much they were willing to pay for premiums to insure their rice and wheat crop yields, and 3) to reveal if there were differences across farmers with different characteristics. Nepal was chosen as a case study due to the presence of an existing insurance scheme. In 2013, the Nepalese government launched an index-based multi-peril crop insurance scheme to support farmers with their yield loss, particularly from droughts and floods (based on area yield), and heavily subsidised it by paying 75% of farmers' premiums. However, as per communication with government officials and various unpublished sources, the uptake of this scheme has been limited, despite farmers facing many risks from EWEs, including detrimental impacts on crop production.

The results of this study will help to set appropriate and fair insurance premiums which are acceptable to farmers, and that attract more farmers to participate in such schemes. The findings will further help to address the question of why the current agricultural insurance scheme has, thus far, had a limited positive impact on farmers. The findings may also be used to design appropriate insurance premiums for insurance schemes in other developing countries.

A contingent valuation (CV) was conducted in the Terai lowlands region of Nepal to address the aims. The Terai lowlands are where the majority of agricultural production in the country take place, with more than 84% of farm households producing paddy rice and 65% producing wheat (CBS, 2011). Only 20% of the total agricultural area in the region is under irrigation, with the vast majority being unirrigated and rainfed, making the agricultural systems highly vulnerable to EWEs (Budhathoki and Bhatta, 2016; Chalise and Naranpanawa, 2016).

Contingent valuation has become a prominent tool for evaluating the effectiveness of index-based insurance schemes in developing countries through farmers' stated willingness-to-pay (WTP). While most CV studies on farmers' WTP for index-based insurance investigated weather indices (Hill et al., 2013; Abbas et al., 2015; Bogale, 2015; Arshad et al., 2016; Fahad and Jing, 2017), very few studies explored WTP for area-based yield insurance (Zhang et al., 2011; Ghahremanzadeh et al., 2017). A study by Guo (2016) investigated weather-index based crop and livestock insurance in the hilly districts of Nepal and found that the annual mean WTP for rice insurance was around 3% of household income. A few CV studies from Nepal exist (eg Devkota et al., 2014; Devkota and Maraseni, 2018) in which flood risks management strategies under different flood hazards scenarios were assessed.

2. Methods

2.1. Study area

The Terai region covers only 14% of the total land area of Nepal, but contributes 72% of the rice and 63% of wheat production (MOAD, 2017). It is, therefore, referred to as the 'granary' of Nepal, as more than 84% of farm households in this region are actively engaged in rice production. The region covers 22 districts (out of the 75 districts of Nepal) and is home to more than half of the country's population of 28.5 million people (CBS, 2011). Based on the recent climate change impact survey by the Central Bureau of Statistics (CBS, 2016) and on discussion outcomes with officials from the Department of Hydrology and Meteorology (DHM), two districts were selected for this study: the Banke and Bardiya districts. The selected municipalities and their respective wards[1] from these districts have, in recent years, been highly affected by EWEs such as floods, heat waves, and cold spells (Maharjan et al., 2011).

2.2. Sampling method

Three wards (5, 8, and 12) of the Gulariya municipality of the Bardiya district were purposively selected, as were three wards (3, 4 and 5) of the Rapti Sonari rural municipality of the Banke district (Fig. 1). From each municipality, farming households were selected using systematic random sampling. A total of 350 household heads or leading household's members were interviewed. Among these sampled households, nearly 52% of interviewed households were located in Rapti Sonari and the remaining 48% in Gulariya. The survey was conducted between the first week of November 2017 and the third week of January 2018 by three experienced and trained research assistants who both spoke Nepali, the primary language used for the survey, and who could also understand Tharu and others local dialects.

Key informant interviews were conducted using a pre-tested semi-structured questionnaire prior to the primary survey to inform the design of the household survey questionnaire and the CV. During the survey, key informants continued to be interviewed in order to complement and interpret results from the CV. Altogether nine key informants were interviewed: three central government officials from the Ministry of Agriculture and Development insurance board, four district level government officials from two district (two from each district) agricultural office, and two representatives from insurance companies (one from each district) who were directly involved in providing agricultural insurance in these areas. The key informants were asked about farmers' existing coping mechanisms in mitigating the impacts of EWEs, the current status of insurance uptake, problems with the existing insurance policies, and for suggestions of how to increase agricultural insurance penetration to poor and marginal farmers.

2.3. An overview of crop insurance in Nepal

The government of Nepal, through the insurance board, introduced crop and livestock insurance directives in 2013 with the aim to encourage insurance companies to develop commercial agriculture insurance schemes. The directives introduced the obligations of non-life insurance companies to offer agriculture insurance, and also introduced guidelines for agriculture insurance that they can use. Along with that, the companies were also free to submit their schemes for the approval of the insurance board (Ghimire et al., 2016). Seventeen out of 19 non-life insurance companies (selected by the Insurance Board of Nepal)

[1] The lowest administrative division in Nepal.

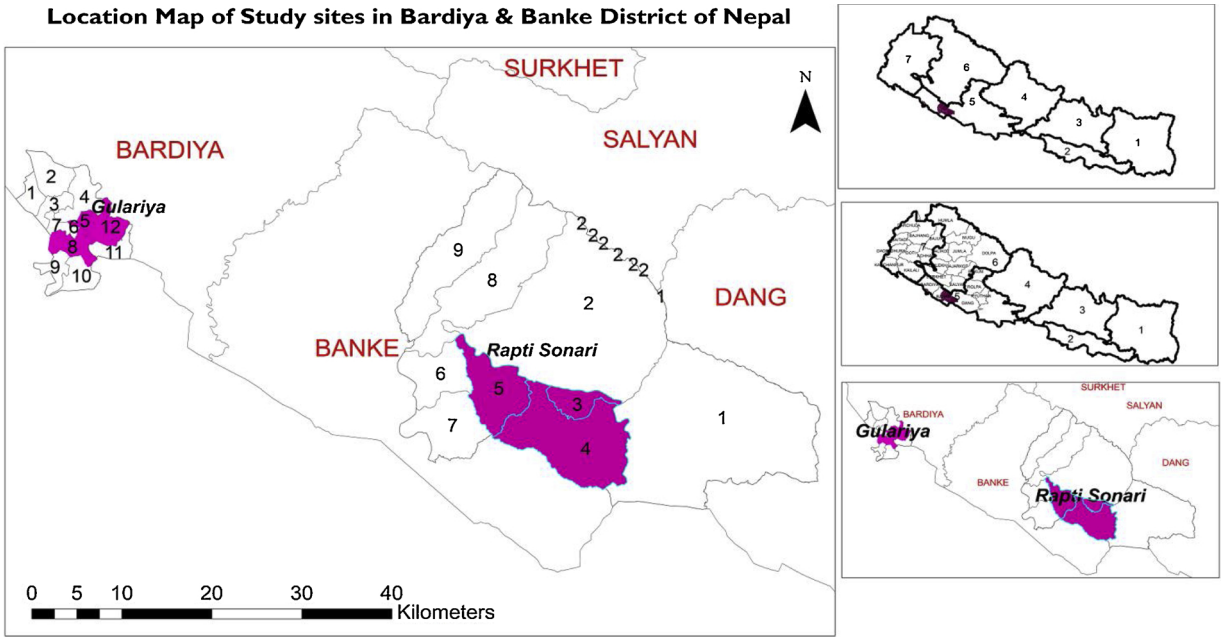

Fig. 1. Study area in the Terai lowlands of Nepal.

currently offer agricultural insurance to farmers.

As of 2013, the current insurance scheme is indemnity based (damaged based) and covers all crops. This means that, based on the damage incurred in the field, indemnity is paid on the basis of the damage in the respective area. The sum insured is based on the cost of production (input-based), while yield estimation is not taken into consideration. The damage is assessed on the individual farm levels. If damage occurs and payouts are granted, the losses that have already occurred to farmers are paid back by the insurance company (Ghimire and Kumar, 2014).

The government of Nepal adopted area-based yield insurance for two crops in 2016: cereal seed crops and spring paddy rice. The reason an area-based yield index was given preferrance over a weather-based index was that it covers yield loss from multiple non-preventable and uncontrollable natural forces (act of god) rather than from a single weather event. The insurance payouts (the indemnity) to policyholders are paid on the basis of the damage to the expected yield in the respective area, not based on the damage to the yield on the individual farm. Payouts of up to 90% of the yield loss are made to farmers if the actual village level yield had been less than the yield projected at the time of purchasing the insurance. Farmers pay a premium of 5% of the expected total yield revenue. The government initially introduced a 50% premium subsidy, which was revised in 2013, and raised to 75% to encourage farmers to take up crop insurance (Ghimire et al., 2016).

2.4. Questionnaire design

The questionnaire for the household survey was prepared based on both the information obtained from the key informants and the current CV literature. The final version was pre-tested with 15 farming households in the study area and finalised after the incorporation of comments received during the pilot testing.

The questionnaire contained three parts. The first part asked for the socio-demographic characteristics and farming background of the respondents; the second part asked about the farmers' perceptions of and experiences with various EWEs, particularly floods, heat waves, and cold spells; and the final part included consisted of double-bounded dichotomous choice questions on farmers' WTP. On average, each interview too took 30 min to complete.

WTP questions were administrated only to those respondents who confirmed that they were interested in acquiring crop insurance.

2.5. Contingent valuation design

Contingent valuation is a stated preference method commonly used to evaluate goods and services that are not traded at markets and, therefore, have no apparent market value; and future products or programs that do not yet exist, and that, therefore, also have no market value (Carson and Hanemann, 2005). As such, CV has been applied in many research areas, including environmental and agricultural economics, health economics, and marketing. It is, in fact, the most commonly used technique for valuing the non-use values or passive values of the environment (Navrud, 1992). Due to the hypothetical nature of CV, the method is susceptible to biases (Navrud and Mungatana, 1994) and therefore contested (Noonan, 2003). Nevertheless, many methods exist to minimise the specific biases, and CV remains the most commonly applied stated preference method.

Different elicitation methods and designs exist, including open-ended and closed (take or leave it) formats, payment cards, and referendums. Single-bounded-dichotomous-choice (SBDC) and double-bounded-dichotomous-choice (DBDC) are the two commonly applied referendum methods (Mitchell and Carson, 2013). The SBDC model is considered as providing less information (Lopez-Feldman, 2012), and comparatively, requires larger samples for accurate model estimations of willingness to pay (Hanemann et al., 1991). Most previous studies on WTP for crop insurances have applied the DBDC design (Hill et al., 2013; Fahad and Jing, 2017).

In this study, the DBDC design was chosen, with a single follow-up bid, a method which minimises the starting bid bias (Hadker et al., 1997). The anchoring bias is also unlikely to occur in DBDC designs because the second bid differs significantly from the first bid (Herriges and Shogren, 1996). The hypothetical bias was further minimised by the use of a short 'cheap talk' script (Cummings and Taylor, 1999). The associated text including the cheap talk was presented to respondents (Table S1 in Appendices).

Each respondent was presented with one initial bid to start with and a follow-up bid (see Verbeek, 2008). Those respondents who were interested in participating in the crop insurance scheme were then asked

"*Are you willing to pay xx (Initial bid) NPR/Kattha*[2] *as a premium for crop insurance*? If the response to the initial bid was "Yes", higher follow-up bids were presented, and if the responses were "No", lower follow-up bids were presented (for details see Table S1 in Appendices).

It was estimated farmers' WTP per Kattha rather than per Bigga, the official unit of land measurement and which is more commonly used by farmers to calculate production inputs and outputs for rice and wheat. Extension officers, however, generally make recommendations, such as for fertilizer or pesticide doses, either in hectare (1.5 Bigha) or Kattha. While hectare is not used in the Terai region, Kattha is widely used among farmers. When the use of Bigga was tested for in the pilot phase, farmers felt uncomfortable with it and could not easily state their WTP in Bigga. The aim, in using Kattha, was to reduce the non-response rate. More than half of the respondents (53%) had land sizes of less than a Bigga (20 Kattha) and approximately 35% of land sizes were less than a 0.5 Bigga (10 Kattha).

2.6. Designing of bids

The CV method has been criticised for the potential impact of the initial bids on the WTP results (referred to as anchoring or starting point bias; see Herriges and Shogren, 1996). The initial bids were therefore carefully designed, and the subsequent follow-up bids were based on the initial bids. As described in this section, the initial bids were based on the premiums of the existing insurance scheme, minimising the starting point bias and leading to realistic WTP results.

To design the initial bids, various primary and secondary information from government and non-government sources were used. Based on this information the insurance premium for both paddy rice and wheat, was decided to be set at 5% of the total revenue (before premium subsidies). The total expected average paddy rice production in the Terai region was 32.72 quintals[3] /ha for 2017 (MOAD, 2016) and the average minimum support price (MSP)[4] for paddy rice was NPR 2,610/quintal (MOAD, 2017). The total expected average wheat production in the Terai region was 26.30 quintals/ha in 2017 (MOAD, 2016) and the average minimum support price for wheat was about NPR 2,800/quintal (calculated based on the 2017 Indian MSP price for wheat). The average total expected revenue of paddy rice and wheat was, therefore, NPR 85,400/ha[5] and NPR 73,640/ha[6], respectively. Since the premium rate was fixed at 5% of the total revenue, the premium for paddy rice used in the design of this study was NPR 4270/ha/season and for wheat NPR 3682/ha/season.

The government of Nepal already offers to pay 75% of the insurance premiums for farmers', and it has discussed whether this should increase to 90% to encourage more farmers to participate in the crop insurance scheme. The initial bids in the design of this study were based on the possibility that, in the long-term, the government will make adjustments to the actual premium subsidy of 75%. It was assumed that the government might increase the premium subsidy to 90%, or reduce it to 50%, 37%, or 25%. The initial bids were then set based on the calculations of the premium amount that paddy rice farmers would be required to pay if the government did not provide them with any subsidy; in which case, farmers would have to pay NPR 144/Kattha[7]. For paddy rice, at different scenarios of premium subsidies such as 90%, 75%, 50%, 37%, and 25% were 15, 36, 72, 54, and 108 NPR/Kattha, respectively. The initial bids for the wheat insurance premium were designed using the same approach. The initial bids for the wheat CV were: NRP 12, 30, 40, 60, and 90 at 90%, 75%, 63%, 50%, and 25%, respectively, of the premium subsidy of the actual premium amount (NPR 125/Kattha).

Lower follow-up bids were approximately 25% lower than the initial bids and higher follow-up bids were more than doubled the lower follow-up bids (Table 1), which were determined after discussions with both government and insurance companies' officials.

2.7. Analysis

Individual *i*'s WTP can be modelled as a linear function:

$$WTP_i\,(x_{i,}\,,\ \varepsilon_i\,) = x_i'\beta + \varepsilon_i \tag{1}$$

Xi, is a vector of explanatory variables which were assumed to have an impact on the WTP, including gender, age, income, education, remittances in the last 12 months, land size, frequencies of floods in the last five years, access to extension services, distance to the river, and proportion of agriculture income of the total household income. β is a vector of parameters to be estimated and ε_i is the error term, assumed to be normally distributed with mean zero and constant variance σ^2. The estimates of β represent the marginal effects of the explanatory variables on the WTP.

To improve the efficiency of the estimation, follow up dichotomous questions were asked after the initial dichotomous question. An individual was expected to accept the offered bid if their WTP was higher than the proposed bid and to reject it if their WTP was less than the proposed bid. The second bid or follow up bid was conditional on the responses of the initial bid.

For simplicity, m^1 denotes the initial bid vehicle; m^{2l} represents the second bid if the individual answers "no" to the first question; and m^{2h} represents the second bid if the individual's response was negative to the first question. y^1 and y^2 are the dichotomous variables, which capture the responses of the first and second questions respectively. Under the assumptions of the Eq. (1), each individual would be in one of the four categories described below (Lopez-Feldman, 2012).

For an individual whose response is 'yes' to the first and 'yes' to the second bid, $m^{2h} \leq \text{WTP} < \infty$. The probability of this case (yes, yes) is given by:

$$pr(y_i^1 = 1,\ y_1^2 = 1|x_i) = pr(1,\ 1) = \ \phi\left(x_i\frac{\beta}{\sigma} - \frac{m^{2h}}{\sigma}\right) \tag{2}$$

For an individual with the answers 'yes' to the first and 'no' to the second bid, $m^{2h} > m^1$, i.e. , $m^1 < WTP \leq m^{2h}$. The probability of this case (yes, no) is given by:

$$pr(y_i^1 = 1,\ y_1^2 = 0|x_1) = pr(1,\ 0) = \ \phi\left(x_i'\frac{\beta}{\sigma} - \frac{m^1}{\sigma}\right) - \phi\left(x_1'\frac{\beta}{\sigma} - \frac{m^{2h}}{\sigma}\right) \tag{3}$$

For an individual with the answers 'no' to the first and 'yes' to the second bid, $m^{2l} < m^1$, i.e. $m^{2l} \leq WTP < m^1$. The probability of this case (no, yes) is given by:

$$pr(y_i^1 = 0,\ y_1^2 = 1|x_1) = pr(0,\ 1) = \ \phi\left(x_i'\frac{\beta}{\sigma} - \frac{m^{21}}{\sigma}\right) - \phi\left(x_1'\frac{\beta}{\sigma} - \frac{m^1}{\sigma}\right) \tag{4}$$

For an individual with the answers 'no' to the first and 'no' to the second bid, $0 < WTP < m^{2l}$. The probability in this case (no, no) is given by:

$$pr(y_i^1 = 0,\ y_1^2 = 0\,|x_i) = pr(0,\ 0) = 1 - \ \phi\left(x_i\frac{\beta}{\sigma} - \frac{m^{2l}}{\sigma}\right) \tag{5}$$

Let D_i^{YY}, D_i^{YN}, D_i^{NY} and D_i^{NN} be dummy variables that represent the relevant cases for each respondent. The values of $\beta\,and\,\sigma$ can be

[2] 1 ha = 29.56 Kattha, 1 Bigga= 20 Kattha.

[3] 1 Quintal =1000 kg.

[4] The minimum support price is fixed by the government of Nepal to purchase directly from farmers. Even if the market price of an agricultural product is below this fixed price, the government purchases the product from farmers at the minimum support price.

[5] Total Value of rice/ha = Rice production in quintal /ha * price/quintal. (32.72*2,610= NPR 85,400).

[6] Total wheat yield value/ha = Average wheat production in quintal/ha * price/quintal (NPR 26.30*2,800= NPR 73,640).

[7] 1 Kattha = 0.034 ha.

Table 1
Bid structure of two contingent valuations used in study (for paddy rice and wheat) to explore farmers' willingness to pay for crop insurance.

Serial Number	Paddy rice (NPR)			Wheat (NPR)		
	Initial Bid value	Follow up lower bid	Follow up higher bid	Initial Bid value	Follow up lower bid	Follow up higher bid
2	15	10	20	60	40	80
1	36	25	50	30	20	40
4	54	37	75	90	60	120
3	72	50	100	40	35	70
5	108	75	200	12	10	20

We used separately randomly selected initial bids (36, 15, 72, 54, and 108) with lower (25, 10, 50, 37 and 75) and higher follow-up bids (50, 20, 100, 75 and 200) for paddy rice insurance, and initial bids (30, 60, 40, 90, and 12) with lower (20, 40, 35, 60 and 10) and higher follow-up bids (40, 80, 70, 120 and 20) for wheat insurance. The initial bids were selected based on information from key informants and the pilot study.

estimated by maximising the log-likelihood function, and the parameters estimation can be estimated by user-written command 'doubleb' in Stata (see Lopez-Feldman, 2012).

$$\begin{aligned} \text{Ln } L= \sum_{i=1}^{N} \{D_i^{YN} \ln\left[\phi\left(x_i'\frac{\beta}{\sigma} - \frac{m^1}{\sigma}\right) - \phi\left(x_1'\frac{\beta}{\sigma} - \frac{m^{2h}}{\sigma}\right)\right] \\ + D_i^{YY} \ln\left[\phi\left(x_i'\frac{\beta}{\sigma} - \frac{m^{2h}}{\sigma}\right)\right] + D_i^{NY} \ln\left[\phi\left(x_i'\frac{\beta}{\sigma} - \frac{m^{21}}{\sigma}\right) \right. \\ \left. - \phi\left(x_1'\frac{\beta}{\sigma} - \frac{m^1}{\sigma}\right)\right] + D_i^{NN} ln\left[1 - \phi\left(x_i'\frac{\beta}{\sigma} - \frac{m^{2l}}{\sigma}\right)\right]\} \end{aligned} \quad (6)$$

The 'doubleb' command incorporates the first bid, second bid, first response, and second response to estimate the WTP as a dependent variable in a model. Two models were estimated for each crop (wheat and rice), the first without control (explanatory) variables and the second with control variables. For the first model, the 'doubleb' command directly estimates β and σ in Eq. (1), and WTP is $\beta\ x_i'\beta$, the constant. A model with no control variables allows the efficient use of the data to estimate WTP under the assumption that there is a single valuation function behind the responses to both bids (Maltese et al., 2017). The second model was estimated by using 'doubleb' command after including control variables. The mean WTP was calculated using the 'nlcom' command after including all the significant explanatory variables in the models, with covariates as mentioned by Haab and McConnell (2002).

To check for multicollinearity among the explanatory variables, the 'collin' command was used to calculate the variance of inflation factor (VIF). As a rule of thumb, a variable whose VIF values greater than ten may need further investigation, if mean VIF value is found to be less than 10 for a model which indicated that there is no issue of multicollinearity (UCLA, 2016).

Selection of variables was based on Wald tests. For the paddy rice model, Wald test results indicated that eight control variables consist of socio-demographic and perception variables on EWEs were jointly significant at the 5% level ($\chi^2 = 25.62$, df = 8 and *P*-value = 0.0012). The same variables were included in the wheat model. The Wald test failed to reject the null hypothesis that all variables were jointly significant ($\chi^2 = 11.71$, df = 8 and *P*-value = 0.16). After excluding some explanatory variables which had low explanatory power in the wheat model, the Wald test result was significant to the 10% level ($\chi^2 = 10.99$, df = 6 and *P*-value = 0.0887).

The selection of the initial bids will have an impact of the estimated WTP (Hanemann et al., 1991). Before estimating the WTP, separate discrete choice models were estimated for paddy rice and wheat in order to test whether the initial bid had an impact on farmers' WTP, along with others control variables. A significant negative impact of WTP indicates that as the premium payment increases, the probability of positive response to the WTP declines (Table S2 in Appendices).

2.8. Variables

Based on previous studies socio-demographic and attitudinal variables were identified which have been hypothesised to affect households' decisions to adopt and pay for index-based agricultural insurance, and are included in the models as control variables (see Table S1 in Appendices). These factors include previous damage experience of extreme weather events, agricultural income as the primary source of household income, distance to the river, proportion of agricultural income of the total household income, age, family size, education, land ownership, farm and off-farm income, and perceptions of occurrence of EWEs in the future (Devkota et al., 2014; Abbas et al., 2015; Fahad and Jing, 2017). The higher the damage experienced from the extreme events in the past, the higher the WTP for EWEs management is expected to be (Devkota et al., 2014). Farmers without any off-farm income are expected to be more likely to take out crop insurance and to have a higher WTP (Arshad et al., 2016). The role of gender in taking out and paying for crop insurance is debatable. Some research showed that female household heads were less likely to pay for crop insurance due to their limited control over economic sources (Hill et al., 2013; Guo, 2016), while others showed that women were willing to pay more for insurance than men to avoid potential flood damages (Devkota et al., 2014). Farmers' WTP for rainfall crop insurance is assumed to be positively related to farm income and to be negatively affected by off-farm income and by the age of the household head (Teshome and Bogale, 2015). Farmers with large land areas were expected to have higher WTP for insurance than those with smaller land areas (Abbas et al., 2015).

The occurrence of EWEs and experience with them positively influence farmers' interests and WTP for them (Abebe and Bogale, 2014; Greatrex et al., 2015). Floods were common in the research area, primarily during the rainy season when paddy rice was grown. The number of floods (the magnitude of floods) and the distance to the floods sources (rivers) were found to be the main influential variables for farmers' WTP for flood insurance (Botzen and van den Bergh, 2012; Devkota et al., 2014; Devkota and Maraseni, 2018). It was, therefore, assumed that farmers would have higher a WTP for paddy rice and wheat crop insurance premiums if they lived near rivers.

Furthermore, living closer to a river makes irrigation easier throughout the year and increases crop productivity. Most of the rainfed lands in the study areas not in river catchments and did not have sufficient irrigation (Devkota and Maraseni, 2018), and thus farmers with less productive and unirrigated lands might be not willing to pay more for crop insurance. However, Abbas et al. (2015) found that the distance to rivers was negatively associated with the WTP for flood risk reductions as living far away from rivers reduces the severity of flood damages. Similarly, Liu et al. (2018) found that the farmers of flooded villages in China were twice as likely to pay index-based insurance as compared to the farmers from non-flooded villages.

It is also assumed that risk perception towards the impacts of EWEs positively influence farmers' uptake of adaptation measures such as crop insurance (Nhemachena and Hassan, 2007; Bryan et al., 2013; Tambo and Abdoulaye, 2013).

A composite variable representing ex-ante perceptions of farmers for three EWEs was, therefore, included: floods, heat waves, and cold spells. Farmers were asked, using a four-point ordinal scale, to rate the likelihood that the EWEs would occur in the next five years (where 0 indicates 'definitely not,' 1 'probably not,' 2 'probably yes,' and 3 'definitely yes').

An ordinal scale question was presented (using four points where 0 indicates 'no damage,' 1 'minor damage,' 2 'some damage,' and 3 'extreme damage') to farmers to indicate their experiences of agricultural

production damages from each of the three EWEs. The arithmetic means for each EWE was then calculated (see Zheng and Dallimer, 2016).

3. Results

3.1. Sample description

The average age of the respondents was 38.7 years (SD: 13), considerably higher than the national mean age of 21.6 years (NRB, 2016) because only adults were interviewed. Approximately 62% were male, and 67% had some formal education. Approximately 78% of the respondents were of Tharus ethnicity, about 10% were schedule caste, and about 7% were Bramin and Chhetri. The average household size was 7.8 persons (SD: 5.31), and farmers' average experience in the agricultural sector was 21.2 years (SD: 12.6). On average, farmers reported to have experienced approximately five floods in the previous five years; and the average distance of respondents' farms and lands from a river was 0.5 km (Table S3 in Appendices).

The average monthly household expenditure was NPR 16,130 (USD 150.6) (SD: 18,000), which was less than the national monthly household expenditure of NPR 25,928 (USD 242.09) in 2016 (World Bank 2016). The annual income was well distributed, with 11% of the respondents having an annual income of less than NPR 50,000 (USD 467), 23% between NPR 50,000 and NPR 100,000 (USD 467–934), 25% between NPR 100,000 and NPR 200,000 (USD 934 − 1,868), 22% had between NPR 200,000 and 300,000 (USD 1868- 2802), and 22% had more than NPR 300,000 (USD 2802). In the previous 12 months, 15% of respondents received remittances from abroad (Table S3 in Appendices).

Key informants reported that only few farming households in the research area currently had crop insurance (10–12 commercial farmers purchased agricultural insurance in Banke before January 2017; as per personal communication with an official from the Banke district agriculture and development office). None of respondents were found, who already had an insurance.

3.2. General interest for crop insurance and reasons for not participating

Almost 84% of the total respondents (350) were interested in purchasing area-based yield crop insurance. Those who declined cited four main reasons: lack of knowledge (28%), lack of own land (28%), administrative hassle (28%), and income constraints (14%). Only 2% stated the possibility of income loss in the future as a reason, and that they thought they were required to pay premiums up-front, but were uncertain about timely payouts, if claimed.

Almost all (99%) of the 350 respondents stated risk sharing or risk transferring of EWE impacts as a reason for their intention to purchase crop insurance, and further stated that crop insurance is an essential question.

3.3. Preferred premium payment options

Among those farmers who were generally interested in crop insurance (293), 87% said that they wished to pay premiums in cash, while 13% preferred in-kind payments due to of cash constraints. Approximately 56% reported that they were willing to pay the premiums right after harvest, 13% preferred to pay them during land preparation, 10% during the sowing of crops, and 8% after sowing.

3.4. Farmers' WTP for area-based yield insurance

Nearly 4% of the 293 respondents rejected both the initial and lower follow-up bids (Table 2) for the insurance. This means that about 96% of respondents gave a positive response to WTP for rice insurance. Likewise, almost 94% were willing to pay for wheat insurance (about 6% rejected both the initial and lowered follow up bids). Table 2 shows the distribution of the accepted and rejected bids for both insurances.

Table 2
Joint frequencies of farmers' responses in contingent valuations (paddy rice and wheat).

Response	Paddy rice		Wheat	
	Frequency	Percentage	Frequency	Percentage
Numbers of No-No Cases	10	3.4	17	5.8
Numbers of Yes-No Cases	69	23.5	59	20.2
Numbers of No-Yes Cases	31	10.7	28	9.5
Numbers of Yes-Yes Cases	183	62.4	189	64.5
Total Respondents	293	100	293	100

The mean WTP for paddy rice insurance premiums was NPR 127.2/Kattha (USD[8] 35.13/ha) per cropping season and NPR 91.6/Kattha (USD 25.30/ha) per season for wheat insurance premiums (derived from the bid-only model; Table 3).

When including control variables, and using the average values for those, the WTP for rice insurance premiums increased slightly to NPR 132.88/Kattha/season, and for wheat insurance premiums to NPR 91.78/Kattha/season (Table 4).

3.5. Factors affecting farmers' WTP

No serious multicollinearity was found among the explanatory variables in the model for rice (mean VIF[9] : 1. 25), nor in the model for wheat (mean VIF: 1.15). The Wald test indicated the joint significance of the explanatory variables and was found to be jointly significant at the 5% level and the 10% level, the rice and wheat models, respectively. This means that both of the models had significant explanatory power. Both the intercepts and estimates of sigma were significant.

For paddy rice insurance, five of the eleven explanatory variables were found to be significant (Table 3). Access to extension services ($p < 0.001$), the frequency of floods in the last five years ($p < 0.05$), and household size ($p < 0.01$) all affected farmers' WTP negatively. Household income ($p < 0.05$) and farm size ($p < 0.01$) both positively affected farmers' WTP.

Two of the nine control variables significantly affected the WTP for wheat insurance premiums. Being male ($p < 0.01$) negatively affected farmers, while the share of agricultural income of the total household income ($p < 0.01$) positively affected farmers' WTP for wheat insurance. Perceived damage of previous EWEs, an expectation of EWEs occurring in the next five years, and agriculture as a major source of earning did not have a significant effect on farmers' WTP for wheat insurance.

Farming households in the higher annual income brackets of more than NPR 300,000 (USD 2802) had a WTP of NPR 153.6/Kattha/season (USD 42.42/ha/season) as compared to NPR 106.9/Kattha/season (USD 29.52/ha/season) of the households whose annual income was less than NPR 50,000 (USD 467), keeping all other explanatory variables constant (Table S4 in Appendices). Gender had an effect on the WTP for wheat insurance premiums, in that female respondents were willing to pay NPR 9.7 Kattha/season (USD 2.67/ha/season) more for wheat insurance premiums than males (USD 26.7/ha/season as compared to USD 24.02/ha/season).

3.6. Other risk management strategies

While this study focused on insurance, farmers were also asked about the other risk management strategies that they were currently

[8] 1 USD = NPR 107.10 (source: https://www.nrb.org.np/fxmexchangerate.php, 8th June 2017).
[9] Variance Inflation Factor.

Table 3
Results of interval regression to explore determinants of farmers' willingness to pay for insurance for paddy rice and wheat.

	WTP for Paddy Rice		WTP for Wheat	
Variables	Coefficients (Model 1)	Coefficients (Model 2)	Coefficients (Model 3)	Coefficients (Model 4)
Constant	127.2***	124.6***	91.6***	82.6***
	(6.1)	(39.7)	(3.9)	(25.4)
Distance to the flood sources (meters)		−0.009		0.001
		(0.007)		(0.005)
Share of agricultural income of total income (categorical)		−6.6		6.4*
		(5.6)		(1.8)
Income from agriculture (dummy)		14.9		5.9
		(24.6)		(14.7)
Floods in last 5 years (numbers)		−0.78**		
		(0.4)		
Damage experience of EWEs in last 12 months (categorical)		1.4		2.06
		(8.8)		(5.6)
Ex-ante perception of EWEs (categorical, 0-3)		3.3		−2.6
		(12.7)		(8.1)
Access to extension services (dummy)		−41.7***		
		(12.2)		
Household income (categorical)		12.8**		2.19
		(5.0)		(2.91)
Family size (numerical)		−2.07*		−1.07
		(1.09)		(0.7)
Male (dummy)		−17.5		−12.0*
		(11.5)		(7.1)
Farm size (numerical)		6.3*		0.5
		(3.6)		(2.2)
Remittances received in last 12 months (dummy)				−14.3
				(9.2)
Sigma	70.15***	65.16***	44.2***	41.6***
	(5.0)	(4.7)	(3.31)	(3.1)
Observations	293	293	293	293
Wald chi-squared		27.95		15.99
Probability > chi-squared		0.0033		0.068

Standard errors in parentheses.
Models 1 and 3 are without control variables and models 2 and 4 with control variables.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 4
Farmers' willingness to pay for insurance for paddy rice and wheat - Results from DBDC model (in NPR per Kattha per cropping season).

	Mean WTP	Std. Err.	Z	P > |z|	Lower bound	Upper bound
WTP for paddy rice (bids only)	127.17	6.05	21.01	< 0.001	115.31	139.03
WTP for paddy rice (with covariate)	132.88	42.07	3.16	< 0.001	50.41	215.36
WTP for wheat (bids only)	91.59	3.88	23.62	< 0.001	83.99	99.19
WTP for wheat (with covariates)	91.78	23.49	3.91	< 0.001	45.73	137.84

Note: 1 ha = 29.58 Kattha, DBDC = Double Bounded Dichotomous Choice.

Table 5
Implemented risk management strategies for coping with the impacts of EWEs in the study area (% of respondents).

Adaptation measures (Implemented)	Type of EWEs		
	Floods	Heat waves	Cold spells
Raising dykes#	34.5		
Shifts from crops to livestock#	4.5		
By changing crop varieties*	10	36.5	47.4
Proper drainage#	37.7		
Raising dams#	62		
Awareness raising*	64.5	37	37.5
Early warning system*	66	32.6	31.7
Changing planting dates*	22.5	31.5	36.5
Using pesticides$		47.7	93.4
By changing crops$		24.5	30.8
Improving irrigation$		96	60.8
Others*	4.3	4.8	3.7

Note: # only for flood adaptation; * for adaptation to floods, heat waves and cold spells; $ for adaptation to heat waves and cold spells.

applying. Key informants stated that farmers have been applying various other farm and non-farm risk reduction measures to reduce the impact of EWEs on agricultural production and these measures differ across the types of EWEs, as shown in Table 5.

The most important off-farm reduction strategies in the case of floods included participating in awareness-raising campaigns (65%) and adopting early warning systems to stay alert of flood damage in the areas (66%). On-farm risk reduction strategies consisted of raising dykes in case of floods (62%), and during heat waves and droughts, improving irrigation facilities (96%), changing varieties (37%) and planting dates (32%), and using pesticides (48%). Applying pesticides was the most frequently mentioned risk management strategies for cold spells (93%), followed by improving irrigation (61%) and changing crop varieties (47%).

4. Discussion

4.1. WTP for rice and wheat insurance

Farmers were willing to pay about NPR 1381 (USD 12.9) more to insure their rice crops compared to their wheat crops (USD 42.42 vs. 29.52/ha/season), which was not surprising as paddy rice is the predominant crop of Nepal.

The estimated mean WTP for paddy rice insurance was 5.3% (NPR 4543) of farmers' estimated gross paddy rice revenue (NPR 85,400/ha/season) and the mean WTP for wheat insurance was 4.3% (NPR 3161) of estimated gross wheat revenue (NPR 73,640/ha/season) even after assuming a 75% premium subsidy. If farmers had taken out the subsidised insurance provided by the Government, they would receive an average payout of USD 169/ha/season in case of rice yield loss and USD 118/ha/season in case of wheat yield loss based on the mean WTP. The average payout would be much more than their actual premium rate of 5% of the total expected revenue yields (rice USD 39.90/ha/season and wheat USD 34.37/ha/season). Although farmers WTP was much higher than the actual premium rate, the uptake of the current scheme was low, as it was found in previous studies (Jensen and Barrett, 2017; Jensen et al., 2017).

4.2. Factors affecting the uptake of crop insurance

Many more factors affected the WTP for premiums for rice insurance than for wheat insurance (Table 3). Those farmers who had access to extension services had a lower WTP for paddy rice insurance than those without access. Intuitively, this was surprising, since it was expected that information about the benefits of agricultural insurances could have been obtained from those services. It is possible that farmers who had access to extension services were more likely to have information on the different risk management strategies and could, therefore, choose from a greater variety of different risk diversification and reduction options (Barrett et al., 2001; Bryan et al., 2009). In that case, a negative relationship would have been expected, as found in Arshad et al. (2016).

A positive relationship was found between income and WTP for rice insurance, but not for wheat insurance, a result which corroborates the previous finding of Danso-Abbeam et al. (2014). Relatively wealthy households are less cash-constrained and can pay higher premiums for agricultural insurance (Tadesse et al., 2017). Similarly, farmers with large plots of land were willing to pay higher premiums to insure their rice crops from potential future hazards. This indicates that there is a clear relation between commercialisation and insurance. Farmers with larger land size were more likely to be affected by EWEs than farmers with smaller plots; hence the positive relationship between WTP and farm size for rice insurance was expected. As stated, one reason that income and farm size did not affect the WTP for wheat insurance could be the lower relevance of wheat in the production systems and the reluctance of farmers' to pay premiums for something less essential to their livelihoods.

Farmers who had off-farm income from remittances were willing to pay lower premiums for wheat insurance than those who do not receive remittances from abroad. This study found that remittances did not have any impact on farmers' WTP for wheat premiums, which contradicts findings of Bogale (2015) and Abbas et al. (2015).

The finding that farmers who had experienced floods in the last five years had lower WTP for rice insurance contrasts with the findings of Fahad et al. (2018), conducted in Pakistan, which found a positive relationship between flood experience and farmers' WTP for crop insurance. Initially, it was expected that there would be a positive relationship since experience usually strengthen the awareness of potential damage (Arshad et al., 2016). The negative relationship may be due to the poor economic conditions of those farmers in the study areas who had experienced more floods, and who, therefore, were unable to pay higher premiums. Another reason might be that farmers were not able to connect the occurrences of past floods to the insurance mechanism and the expected payouts. The past damages experience with previous EWEs had no impact on farmers' WTP, which could be because wheat and rice crops were less affected by these EWEs in 2016. Farmers' expectations of future EWEs also did not have a significant impact on farmers' WTP for insurance for either crop.

Based on the wheat model, it was found that a male household head had a significant negative impact on WTP for crop insurance. It indicates that the probability of WTP for wheat insurance for a male is lower than that of the female household head. This study was conducted in the Tharu community, in which women are more empowered and highly aware of agricultural insurance and climate hazards. These results are consistent with the finding of Devkota et al. (2014), which suggest that women are more concerned about future impacts of extreme events than men, and thus have a higher level of WTP for crop insurance than men. This and the fact that extension services specifically target women could be the reason for this gender effect. Family size is negatively associated with WTP paddy rice insurance, suggesting that in larger households there might be less disposable income to pay for insurance premiums, as confirmed by Danso-Abbeam et al. (2014). However, the findings of this study contradicted the earlier findings of Arshad et al. (2016), which found that family size positively related to the demand for crop insurance. This study also found that the higher the proportion of agricultural income of the total household income, the higher the WTP for wheat insurance, as confirmed by Arshad et al. (2016) and Devkota et al. (2014), because income from crop agriculture is usually the primary source of household income and, therefore, needs to be protected against EWEs.

4.3. Reasons for not purchasing crop insurance

The major impediments for farmers to purchasing crop insurance were a lack of understanding of the scheme, a lack of trust to the insurance providers, and cash-constraints, as confirmed elsewhere (Binswanger-Mkhize, 2012; Cole et al., 2013; Carter et al., 2014). Despite being fully aware of the insurance schemes, some farmers were not interested due to the arduous and cumbersome administration associated with it, as well as the excessively complicated documentation and paperwork needed for claims (Jin et al., 2016). Another reason that farmers did not want crop insurance is the expectation of a payout delay after a claim is made. This mismatch between farmers' expectations and actual payouts has been highlighted previously as the main reason for the low uptake (Ghimire et al., 2016; Johnson et al., 2018).

Many respondents felt that their small land sizes (28%), fragmented land (28%), and lack of land ownership (renting; 28%) also provided little incentive to purchase crop insurance, consistent with previous findings (Abbas et al., 2015). They further reiterated that they grow multiple mixed crops in the same land in one season, such as pulse types with paddy rice, which could be another issue when buying single crop contracts. Income constraint is considered to be the fourth main reason for unwillingness to take part in the insurance market, as farmers from the study areas were found to be poor, and thus could not afford to buy crop insurance.

Another main reason is the competing risk-mitigation strategies (also see Binswanger-Mkhize, 2012). Crop insurance is only one of many risk management strategies and one that distributes the risk rather than reduces it. Farmers might be aware of this and prefer other risk reduction strategies. When participating in the insurance scheme, farmers would, on the one hand, save costs and time by not attempting to respond to the impacts of EWEs on their crops. On the other hand, they would increasingly rely on the insurance payouts and minimise their efforts to adopt innovative ways to optimise crop production.

4.4. Impacts of premium subsidy on the government's budget

Providing the generous subsidy of 75% is already costly for the government. The risk is that the budget will blow out beyond control if many more farmers participate in the scheme. The subsidies are therefore unlikely to be sustained in the long run. In the 2017/2018 fiscal year, the government allocated NPR 350 million (USD 3.2 million) to pay the premium subsidy for both livestock and crop insurance and this share is expected to increase in the next few years if subsidised insurance policies are in place and as more farmers become aware of the scheme. In the 2015/2016 fiscal year, 1,362,908 ha was used for rice production and 745, 823 ha (MOAD, 2016) for wheat production. Based on the average WTP for rice, the government allocation of USD 3.2 million in the 2017/2018 fiscal year will be sufficient enough to insure 25,145 ha of rice if the allocated budget is used to insure rice only under the current subsidy scheme. If all rice growers were to purchase insurance, the government would need to allocate NPR 18.5 billion (USD 173.4) solely to rice premium subsidies. If all wheat growers were to take up the insurance, the government would need to spend NPR 7.07 billion (USD 66.05 million) to wheat premium subsidies, only.

5. Conclusion, policy implication and recommendations

The primary objective of this study was to assess farmers' interest in, and WTP for, area-yield based crop insurance in the Terai lowlands of Nepal. Crop insurance can share the risks of financial damages from yield losses after extreme weather events, but its rate of adoption remains very low in developing countries. This study was undertaken under the premises that the Nepalese Government heavily subsidised farmers' participation in crop insurance schemes, but that the uptake has remained very low. Results of a contingent valuation revealed that respondents who did not intend to join the crop insurance scheme did so because of a lack of knowledge, the complex administrative procedures, and cash-constraints. Moreover, those farmers who wanted to join would prefer to pay insurance premiums after harvesting their crops. About 87% respondents preferred to pay their premiums in cash, while the other 13% wanted to pay them in-kind, due to limited cash availability. Farmers' mean WTP for premiums was about NPR 4543/ha/season (USD 42.42) for paddy rice, and NPR 3162 ha/season (USD 29.52) for wheat, assuming that the government continues to pay 75% of the premiums.

The majority of farmers (84%) were interested in purchasing crop insurance, and were willing to pay much more of the premiums than they currently did under the subsidised scheme. It was estimated that their WTP for rice insurance premiums was still about 5.3% of the gross rice revenue per season, and the WTP for wheat insurance was about 4.3% of the wheat revenue per season (assuming that farmers only paid 25% of the premiums). Income was a strong determinant of farmers' WTP, suggesting that the most impoverished farmers had the most substantial impediments to join. It is, therefore, unlikely that the price of the premiums, even if the subsidy were to be reduced, is the only impediment for farmers participating in the scheme.

Of respondents, 28% were not familiar with the crop insurance mechanism, suggesting that there is a definite need for training (such as orientation programs) of farmers and village leaders, which might then lead to higher insurance uptake (Dercon et al., 2014). The raising of awareness and reducing the ignorance of future damages from climate variability might also increase the uptake (Treby et al., 2006; Greatrex et al., 2015). At the same time, the tedious administrative processes should be simplified to bring a maximum number of farmers into the insurance scheme.

Given that the Nepalese Government is unlikely to sustain the generous subsidies if the uptake of the crop insurance increases substantially, it is essential that farmers are attuned to the possibility of purchasing the insurance without the subsidies – to pay 100% of the premiums themselves once the insurance scheme has been widely established. To minimise the risk for the government for uncontrolled costs when many more farmers join the scheme, it is suggested that the government could 1) start reducing the premium subsidy to 50%, 2) make the subsidy means-tested (income and land size), and 3) encourage the larger farms to become more commercialised. The 75% premium subsidy could still be paid for the poorest farmers. Furthermore, losses from the impact of EWEs varies across regions, and this factor also warrants more flexible subsidies, away from the current uniform premium structure, which might not be suitable in the context of Nepal.

The mismatch between farmers' expectation can be minimised by closely working together with the insurance providers. Trust of insurance companies needs to be strengthened by removing supply-side constraints, such as offering reliable weather data and crop risks model to assess catastrophic risks exposures. The government should also play an essential role in providing farmers with awareness and insurance education to support the marketing and promotion of private insurance providers (Mahul and Stutley, 2010).

Finally, insurance providers might face liquidity problems and solvency in the long run due to climate change-related increases in EWEs and spikes in payouts. Key-informants pointed out that a lack of technical workforce and the issue of moral hazards are future impediments to providing affordable insurance. The government should create an environment of reinsurance and further assistance in the future by offering financial incentives to providers to ensure the viability of their businesses, but without over-benefiting them. The government has to bear in mind that there are other risk management and reduction strategies that farmers adopt and for which they might need support. The insurance premium subsidy provision puts a high financial burden on the government, which will ultimately fall on the general taxpayers. Focusing too much on risk sharing and the provision of agricultural insurance might hamper risk mitigation and adaptation in the long run (Skees et al., 2008).

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.landusepol.2019.03.029.

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